Resolution Enhancement of Biomedical Images to Augment Analysis

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ABSTRACT
The field of biomedical image analysis is extremely broad and resolution enhancement is a fundamental aspect of virtually every implementation of an image analysis and visualization solution. Enhancement is a system component of all medical imaging modalities and a basic part of many diagnostic applications. Resolution enhancement can significantly aid diagnosis by highlighting regions and accentuating image characteristics, which may be lost in the enormous complexity of a biomedical image. Super resolution imaging technique reconstructs a high resolution image from a set of low resolution images that are taken from almost the same point of view. Super resolution algorithms work in two main phases: an image registration to align input images, and a reconstruction to reconstruct the high resolution image from the aligned images. If the low resolution images are under sampled and have aliasing artifacts, the performance of standard registration algorithms and in turn of interpolation decreases. The key challenge is estimating the high frequency values more accurately in the high resolution image. In this paper, we present a method for the reconstruction of a high resolution image from a set of under sampled and aliased images. In this paper we assume that the motion between low resolution images is a global one; shift and rotation. We suggest a wavelet based interpolation that decomposes image into correlation based subspaces and then interpolate each one of them independently. This information we have intelligently extended in high frequency bins to make edges look shaper. Finally we combine these subspaces back to get the high resolution image. We propose it for super resolution imaging along with results to put forth that it produces best results.

Key words
Biomedical, High Resolution, Image Interpolation, Low Resolution, Super Resolution and Wavelet

1. INTRODUCTION
Digital camera has limitations over spatial and temporal resolution. Over the last few years or so, first-generation wavelets have been used to realize super resolution from a captured sequence of low-resolution (LR) frames. The aim of super resolution is to create high-resolution image of regions, which are sampled in multiple frames. Often video sequences contain substantial overlap between successive frames, and each region in scene appears in multiple frames. For still scene, multiple images with shift/ rotate can be obtained. Most of super resolution algorithms, work in two steps: motion estimation and projection of low resolution pixels onto high resolution grid. Super resolution algorithms estimate the motion vectors by refining the frames or with transmitted motion vector. When a good estimate of shift and rotation between all low resolution frames is available; algorithms find the pixel location of all the low resolution images and then project them on high resolution grid by various interpolation techniques[7]. The interpolation methods based on linear interpolation suffer from some typical artifacts: blurriness, ringing effects, and jagged edges [4]. The nonlinear interpolation algorithms Like NEDI [5] provide good quality but are complex and are often executed for areas like edges only. In this paper, we propose algorithm for the projection step based on assumption that the motion between low resolution frames is a global one; shift and rotation. We propose wavelet domain based frequency content based adaptive interpolation. Wavelet is capable of accurately modeling the statistical behavior of real world images by exploiting relationships between coefficients in different scales. Once registration is done, our algorithm works in two steps: enlargement and adding details. In the enlargement we decompose image into a collection of correlated components and then stretch those to enlarge the image. For stretching we use adaptive interpolation. This solution establishes a practical foundation for adaptive interpolation based on local auto correlation estimates. Quantitative fidelity analyses and visual experiments prove that it outperforms several super resolution as well as popular interpolation techniques.

Along with common image processing applications, the field of biomedical and diagnostic imaging has undergone revolutionary development in last two decades. Imaging procedures and modalities have now become universally accepted clinical procedures after enormous research. The applications include computerized topography (CT), magnetic resonance imaging, ultrasound imaging, nuclear medicine imaging, computerized hematological cell analysis, and so forth. In the past, the conventional and relatively simple image processing techniques such as image enhancement, gray-level mapping, spectral analysis, region extraction have been modified for biomedical images and successfully applied for processing and analysis. The role of image enhancement, gray-level mapping, and image reconstruction from projections algorithms in CT and other radiological imaging modalities is well evident. The significant computational overhead associated with the iterative reconstruction process of biomedical imaging is one of the major factors that hinder its application in clinical diagnosis, especially for large tissue volumes. Recently, many advances in biomedical image processing, analysis, and understanding algorithms have shown a great potential for enhancing and interpreting useful diagnostic information from these images more accurately. The paper presents a general purpose biomedical optical image reconstruction model along with results obtained through the iterative image reconstruction process to control the image resolution the sub domain of interest, and hence to detect interior targets, such as tumors, from the discrete measurements collected on the surface of clinically relevant tissue. The proposed image reconstruction provides a means to detect small targets and improve the image quality.

The paper is organized as follows. In section II, we discuss concepts related to super resolution imaging and phases: registration and interpolation. Section III we present proposed adaptive interpolation technique. We pick few images and show results of proposed technique in section V. Conclusions are presented in section VI. Sections VII and VIII are acknowledgment and references respectively.

2. SUPER RESOLUTION

In most imaging applications, images with high spatial resolution are desired and often required. Resolution enhancement from a single observation using image interpolation techniques is of limited use because of the aliasing present in the low-resolution (LR) image. Super-resolution(SR) refers to the process of producing a high spatial resolution(HR) image than what is afforded by the physical sensor through post processing, making use of one or more low resolution observations. It includes up sampling of the image, thereby increasing the maximum spatial frequency, and removing degradations that arise during the image capture, namely, aliasing and blurring.

Let us define image formation model. Image formation is defined as a cascade of filter operations. There is an overall blur applied at each pixel that can be decomposed as sequence of operations: blurring, wrapping, degradation, spatial sampling and quantization. With reference to such image formation model, super-resolution is defined as the use of multiple images and/or prior model of information to recover an approximation to image better that what would be obtained by image reconstruction followed by debluring using knowledge of kernel of blur. In other words, we can define super-resolution as process of approximating the image at a larger size with reasonable approximation for frequencies higher than those representable at the original size. Also further a finer sampling and debluring obtains a super resolution with increased spatial resolution.

Super resolution has importance for video sequence. A video camera has limited spatial and temporal resolution. The spatial resolution is determined by the spatial density of the detectors on the imaging plane and by their induced blur. These factors limit the minimal size of spatial features or objects that can be visually detected in an image. The temporal resolution is determined by frame rate and by the exposure time of the camera. These limit the maximal speed of dynamic events that can be observed in a video sequence. In many applications like video surveillance, high-resolution images are crucial. Another interesting application is in video compression. The low-resolution video is transmitted and high-resolution video is generated at the receiving end. Motion video has large number of images in it and super resolution can be used to extract action packed images from it, which otherwise very difficult to capture using a still camera. This has application in sports photographs, movie posters and so forth. Scientific applications include astronomy, medical imaging and many more.

Super-resolution involves two steps: Registration and Interpolation along with image restoration. With different approaches with common goal most of super resolution techniques try to solve these two steps. Using multiple low resolution images, registration step tries to compute motion estimation. Motion estimation is used to estimate the pixel positions of LR images with respect to reference LR image. Reference image is one of the LR images. These pixel positions take any real value also. Once registration is done accurately, this information is projected on to a desired HR grid, also known as interpolation.

2.1 REGISTRATION

All the images are to be first aligned in the same coordinate system by registration phase. Precise sub pixel image registration is a basic requirement. For registration we extend the work of [32]. We have done registration at spatial domain. Our algorithm is based on the fact that, two shifted images differ in frequency domain by phase shift only. This can be found by using correlation between them. We have iteratively shifted each image by very small angle and compared with reference image for correlation between them. We continue till we get highest correlation and note the shift. We implemented this technique in Matlab 7.1 using built-in correlation instruction.

2.2 INTERPOLATION

Interpolation is one of the important phases of super resolution process. The HR image quality highly depends on interpolation technique used. Image interpolation is the process of defining a spatially continuous image from a set of discrete samples. It is a process of determining the values of a function at position lying between its samples. It achieves this by fitting a continuous function through the discrete samples; which evaluates the input values at arbitrary positions along with defined sample positions. Interpolation is commonly implemented by convolution of an image with a small kernel for the weighing function. While sampling generates an infinite bandwidth signal from one which that is band limited; interpolation reduces the bandwidth of a signal by applying a low pass filter to the discrete signal. Thus interpolation reconstructs the signal lost in sampling by smoothing the data samples with an interpolation function. The process of super resolution is based on the assumption that all pixels form available frames can be mapped back onto the reference frame, based on the motion vector information, to obtain an up-sampled frame. In the registration stage, the relative shifts between LR images as compared to the reference image are estimated with fractional pixel accuracy. Obviously, accurate sub pixel motion estimation is a very important factor for reconstructing good quality super resolution images. As a shift between LR images is arbitrary, the registered HR image will not always match up to a uniformly spaced HR grid. Thus a non-uniform interpolation is necessary.

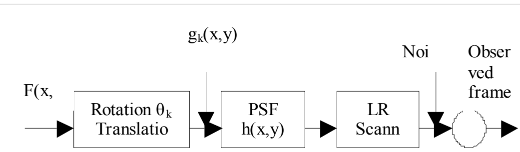


Fig 1. Observation Model to relate HR image & LR image

The fig.1 shows the observation model relating a high-resolution image to low resolution observed images. The input signal *f(x, y)* denotes the continuous (high resolution) image in the focal plane coordinate system *(x, y)* [5]. In fig. 1, the convolution of $g_k(x, y)$ with blurring kernel *h(x, y)* is modeling optical blur. Here motion is modeled as a pure rotation $\Box_k$ and translation T_k. The shifts are defined in terms are *LR* pixel spacing. This step needs interpolation as sampling grid changes in geometric transformation. Also, the transformed signal finally undergoes the LR scanning followed by addition of noise yielding the LR k^{th} frame $y_k(x, y)$.

In order to obtain a uniformly spaced up-sampled image, interpolation onto a uniformly sampling grid is done. Hence in literature of SR, (also in this paper) the term interpolation refers to the process of computing samples of the HR image form LR images either in spatial or in the frequency domain.

3. INTERPOLATION FOR RESOLUTION ENHANCEMENT

Super resolution method restores HR images. In this paper we consider the interpolation as one of the fundamental step in active super resolution. Our interpolation is two-step process: enlargement and adding additional contents. In enlargement, we decompose an image into a set of basis functions, and then stretch those basis functions using adaptive directional interpolation independently. Finally combine all stretched functions to construct a HR image. The method is based on assumptions that the continuous image is a linear combination of continuous scaling functions. We use wavelet for decomposition.

3.1. Decomposition Of Image Using Wavelet

As edges play an important role in perception, due emphasis is to be given while processing them. The perceptually relevant features are to be extracted and interpolated separately. It is needed to preserve the output from introducing any perceptual artifacts, mostly at object boundaries. Requirement is to take care of neighborhood structure especially at the grid points at boundaries. Most of the interpolation techniques are based on approximations with respect to neighboring pixels that leads to blur or blocking effect. This effect is more prominent when the neighboring pixels are not correlated. The technique is needed that would perceptually group the features and treat them individually as per their perceptual relevance.

Recently wavelet has emerged as a promising tool for image processing. We use wavelet transform to decompose N × N image into four subspaces. By stretching each we want to construct image of size 2N × 2N. In one-iteration of process, we estimate coefficients for each subspace. This decomposition is based on structural correlation. The correlation factor we used is frequency component to preserve structural relationship. Aim is to test few mutually exclusive conditions for pixel's luminance value with respect to its surrounding pixels to find the structural relationship. Test should correlate the pixels and accordingly group them. Wavelet transform takes care of this. The image is decomposed into horizontal, vertical, approximate and diagonal components. We use wavelet (db4) for this decomposition. Further we analyze diagonal component to logically decompose it into two diagonals SW-NE and NW-SE to interpolate them separately. Each of basis function is stretched to enlarge the image using our adaptive directional interpolation.

The decomposition phase has two filters: low pass and high pass. These filters separate the input signal into low and high frequency components. The two-dimensional signal first filtered row wise, and down sampled by the amount of two. Then, the procedure is repeated for the column components of two-dimensional signals. This process is called as wavelet decomposition of two-dimensional signal. The low frequency components of row and column of two-dimensional signals are known as approximations, low frequency components of row and high frequency components of column of two-dimensional signal are known as horizontal details, high frequency components of row and low frequency components of column of two-dimensional signal are known as vertical details, and high frequency components of row and high frequency components of column of two-dimensional signal are known as diagonal.

3.2 ADAPTIVE DIRECTIONAL INTERPOLATION

After decomposition, each of the components is enlarged using interpolation. Our interpolation is based on the fact that interpolation works best when it is done along edges and not across. Here for each pixel that needs to be interpolated we consider the likelihood of that pixel belonging to that edge. More weight is given to the pixel lined up along the edge than the pixels across the edge. We call our interpolation method adaptive as our algorithm selects and uses the interpolation kernel depending on the nature of each decomposed component.

We formulate problem as

$$FX=Y \qquad (1)$$

Where X is the HR image to be constructed from the registered LR grid Y and F is the down sampling operator typically consisting of decimation d following a low pass filter H:

$$F=dH \qquad (2)$$

Here the choice of low pass filter depends on a point-spread function (PSF) of imaging system that produced LR image. As imaging system we assume to be unknown and we use adaptive technique to select suitable operator H for filter.

The interpolation of one-dimensional signal is defined as

Where k(x) is the interpolation filter, h is sampling step. In a two dimensional case, the interpolation typically performs separately along each axis. The popular weight functions are box filter (nearest neighbor), text function (bilinear) Gaussian filter and bicubic interpolation [6].

In our interpolation process, the values at stretched basis functions are estimated by a weighted average or convolution of neighboring image samples. The weighting function used in convolution is called the kernel. The kernel is derived as a one-dimensional function. Adaptive convolution imposes constraints to ensure continuity and smoothness leaving one parameter that can be used to tune the kernel for the image. Each subspace is interpolated independently using different kernels depending on nature of component. The numerical accuracy and computational cost of interpolation algorithms are directly tied to the interpolation kernel. As a result, interpolation kernels are target of the algorithm design. The ideal interpolation for point say A (x, y) should be 1-D interpolation in x-direction first by four one-dimensional interpolations. They should be then used for the final 1-D interpolation in y-direction.

1: Approximate components have low frequency contents. The interpolation here is extension of 1D interpolation. The interpolation kernel is defined as:

$$H_a(x,y)= h(x).h(y) \qquad (4)$$

Here
$$h(x) = 1 \qquad 0 \le |x| < 0.5$$
$$= 0 \qquad 0.5 \le |x|$$

$$h(y) = 1 \qquad 0 \le |x| < 0.5$$
$$= 0 \qquad 0.5 \le |x|$$

The frequency response of kernel is

$$H(\omega) = \sin c\left(\frac{\omega}{2}\right) \tag{5}$$

2: Diagonal Component has high frequency components. The kernel is defined as:
$H_d(x,y)$ =h(x).h(y) (6)

$$h(x) = \frac{1}{6}(3|x|^3 - 6|x|^2 + 4) \qquad 0 \le |x| < 1$$
$$= \frac{1}{6}(-|x|^3 + 6|x|^2 - 12|x| + 8) \qquad 1 \le |x| < 2$$
$$= 0 \qquad 0 \le |x|$$

And

$$h(y) = 1 - |x| \quad 0 \le |x| < 1$$
$$= 0 \qquad 1 \le |x| \tag{7}$$

The frequency response

$$H(\omega) = \sin c^2\left(\frac{\omega}{2}\right) \tag{8}$$

3: Horizontal subspace has low frequency horizontal components and high frequency vertical components. The kernel for is defined as :
$H_h(x,y)$ =h(x).h(y)

Here
$$h(x) = 1 - |x| \quad 0 \le |x| < 1$$
$$= 0 \qquad 1 \le |x| \tag{9}$$

and

$$h(y) = (a+2)|x|^3 - (a+3)|x|^2 + 1 \qquad 0 \le |x| 1$$
$$= a|x|3 - 5a|x|2 + 8a|x| - 4a \qquad 1 \le |x| < 2$$
$$= 0 \qquad 2 \le |x|$$

4: Vertical subspace has low frequency vertical component sand high frequency horizontal Components. The kernel is defined as
$H_v(x,y)$ =h(x).h(y)

Here

$$h(x) = (a+2)|x|^3 - (a+3)|x|^2 + 1 \qquad 0 \le |x| 1$$
$$= a|x|3 - 5a|x|2 + 8a|x| - 4a \qquad 1 \le |x| < 2 \tag{10}$$
$$= 0 \qquad 2 \le |x|$$

And
$$h(y) = 1 - |x| \quad 0 \le |x| < 1$$
$$= 0 \qquad 1 \le |x|$$

4. RESULTS

Both the consumer and commercial electronics evolve, wide set of applications as diverse as biomedical imaging, biometric, medicine, digital photography among many other, it is essential to that SR software should be both accurate and robust, which in turn requires a standardized methodology for testing SR imaging algorithms and innovative means to tackle quantifying and automatically resolving issues relating to algorithm functioning. We have implemented and tested our technique in Matlab 7.1. It has been tested on set of images. Results for few biomedical images are presented here.

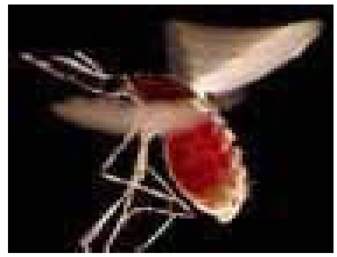
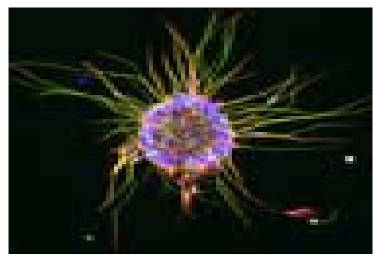


Fig. 1 Low resolution Biomedical Images



F. 2 Low Resolution Image

Fig. 3 Low Resolution Images

Images shown in figure 1-3, represent original low resolution biomedical images and fig 6-8 are low eye image and resultant high resolution image along with zoomed cropped area for both bicubic interpolated and output image of proposed algorithm. The proposed algorithm gives good results for sharp edges too as seen across eyelashes in fig 10. The algorithm has been tested with variety of images, which include biomedical images, mammogram, computer generated images and natural images.

For image quality measure there are two commonly used techniques: Objective evaluation and Subjective evaluation. We have used both objective (MSE, PSNR, MSSIM) and subjective (Mean Opinion Square-MOS) measure for image quality measure. And have proved to be better as compared to conventional interpolation methods.

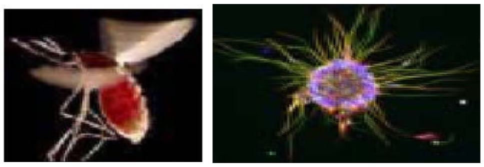


Fig. 4-6 Sample Biomedical Low Resolution Images

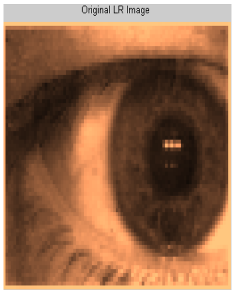


Fig. 6 Original LR Eye

Fig. 7 Resultant SR Eye

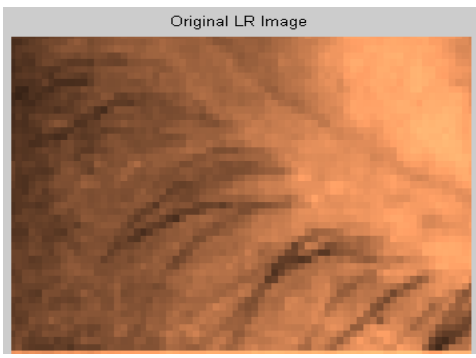
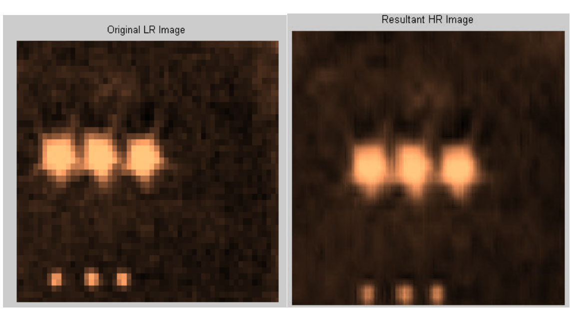


Fig. 9 Cropped and zoomed eyelashes region for high

The Subjective measure with 20 observers was found to be better for all images except text image. It is based on Human Visual System, which allow a better correlation with the response of the human observer. Because characteristics of the edges in many applications such as in medical image are to be reserved for many scales of resolution and edges are always important for human vision, our wavelet based technique preserves the local edge structure to prevent the blurring and blocking effects in reconstructed high-resolution image.



a) bicubic interpolated image b) resultant image

Fig. 8 Cropped and zoomed region

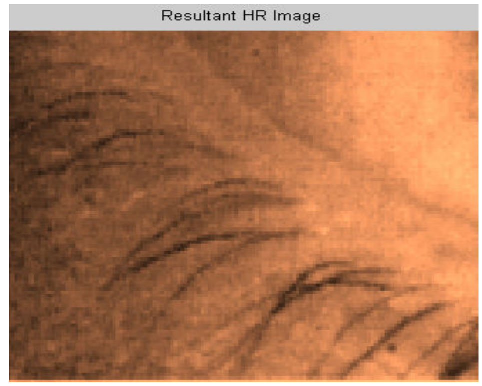


Fig. 10 Cropped and zoomed eyelashes region for resultant high resolution image

5. CONCLUSION

From experimental results it is observed that the proposed method is competitive or rather better in quality and efficiency with the existing interpolation methods. The proposed method has been compared to bicubic interpolation, pixel replication and many others. From the experimental results, we found that the proposed technique is useful for natural and computer generated images. We are currently working on two extensions of our work: incorporating more details in the image by super resolving the image to higher factor using further decomposition of wavelet components. Image quality is one of the important factors in image processing applications and it is a critical aspect in image processing.

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